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UNCERTAINTIES IN LCA

A protocol for horizontal averaging of unit process data—including estimates for uncertainty

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Abstract
Purpose Quantitative uncertainties are a direct consequence of averaging, a common procedure when building life cycle inventories (LCIs). This averaging can be amongst locations, times, products, scales or production technologies. To date, however, quantified uncertainties at the unit process level have largely been generated using a Numerical Unit Spread Assessment Pedigree (NUSAP) approach and often disregard inherent uncertainties (inaccurate measurements) and spread (variability around means).
Methods A decision tree for primary and secondary data at the unit process level was initially created. Around this decision tree, a protocol was developed with the recognition that dispersions can be either results of inherent uncertainty, spread amongst data points or products of unrepresentative data. In order to estimate the characteristics of uncertainties for secondary data, a method for weighting means amongst studies is proposed. As for unrepresentativeness, the origin and adaptation of NUSAP to the field of life cycle assessment are discussed, and recommendations are given.
Results and discussion By using the proposed protocol, cross-referencing of outdated data is avoided, and user influence on results is reduced. In the meantime, more accurate estimates can be made for horizontally averaged data with accompanying spread and inherent uncertainties, as these deviations often contribute substantially towards the overall dispersion.
Conclusions In this article, we highlight the importance of including inherent uncertainties and spread alongside the NUSAP pedigree. As uncertainty data often are missing in LCI literature, we here describe a method for evaluating these by taking several reported values into account. While this protocol presents a practical way towards estimating overall dispersion, better reporting in literature is promoted in order to determine real uncertainty parameters.

Keywords LCA · LCI · NUSAP · Uncertainty · Variability

1 Introduction

Life cycle assessment (LCA) results are commonly presented as point values without even giving a qualitative indication of the underlying uncertainties (Björklund 2002; Ross et al. 2002). Results of LCAs are also strongly influenced by the LCA practitioner, and even ISO 14044 (ISO 2006) compliant studies describing identical systems may experience an order of magnitude difference in assessed impacts (de Koning et al 2009; Williams et al. 2009; da Silva et al. 2010). This practice easily results in unstable conclusions, which subsequently attract criticism and may put public trust in LCA results at risk (Williams et al. 2009; Lazarevic et al. 2012). Desired advancements in the field of LCA are therefore to reduce practitioner influence and to produce uncertainty ranges around life cycle inventory (LCI) results.

Part of the divergence in LCA outcomes relates to different methodological choices made by practitioners. These may include different views on system boundary setting, inclusion of capital goods, allocation, biogenic carbon handling and storage, end of life of products, land use change and characterisation factors (Finkbeiner 2009; Henriksson et al. 2011). In

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theory, however, all of the above can be resolved by a common set of product category rules (de Koning et al 2009). Collecting representative LCI data, on the contrary, is like hunting a moving target as processes constantly change or experience natural variance. Available data for individual unit process flows therefore often remain outdated or of otherwise limited quality. The sourcing of representative unit process data is, moreover, influenced by value judgements, epistemological perspectives and ethics, which may further influence results (Lazarevic et al. 2012). Additional dispersion around averages, in the form of spread, is also introduced by the process of *horizontal averaging*. In the field of LCA, horizontal averaging is commonly performed when multiple unit processes, or aggregated datasets, are combined to represent a more general process (UNEP 2011). This may, e.g. be the averaging of thermal efficiencies amongst coal power plants in a country towards a countrywide average.

Producing uncertainty estimates around results requires input parameters and a propagation method (Fig. 1). Many methods for propagating statistical uncertainties around LCI results were proposed already at an early stage of LCA development, including Monte Carlo analysis, analytical error propagation and fuzzy logic (Heijungs 1996; Huijbregts et al. 2001; Lloyd and Ries 2007). Meanwhile, their application has so far been sporadic due to limitations in quality and quantity of input parameters, time, computing, etc. Most of these hurdles can, however, today be overcome; uncertainty information is becoming more and more available in background data, software allow for the adoption of ranges and computing power has improved. Still limited, however, are clear definitions of how the input parameters should be defined and what they need to enclose.

Uncertainty is dynamic, and it is of importance to identify all of its origins. Already in 1996, Heijungs made a distinction between uncertainties (lack of knowledge) and variability (likely to change often) at the unit process data level. Huijbregts (1998a) later classified these into parameter uncertainty, model uncertainty, spatial variability, temporal variability and variability between objects or sources. Variables are, moreover, subject to covariance (e.g. the causal relationship between amount of fertilizer applied and total yield), directional over time (e.g. efficiency improvements) and influenced by their own previous predictions (e.g. climate predictions can influence climate negotiations, which in turn influence climate).

Applied and interdisciplinary sciences, including the field of LCA, are goal-oriented disciplines, in which social values, ethics, policies, managers, funders, competition and personal beliefs become unavoidable forces that may influence scientific results (Funtowicz and Ravetz 1990; Ravetz 1999; Lazarevic et al. 2012). These underlying forces have motivated the concept of *post-normal science*, where uncertainty is endorsed to be managed, and values are made explicit (Table 1) (Funtowicz and Ravetz 1990). In the field of LCA, this can be related to, e.g. the user influence on results or the often more available access to inventories describing improved or alternative production methods (e.g. organic farmers are often more keen to share their production practices than non-organic farmers). In order to acknowledge these inferences, Funtowicz and Ravetz (1990) introduced the *Numeral Unit Spread Assessment Pedigree* (NUSAP) approach. The NUSAP approach supplements traditional quantitative uncertainty parameters (numeral, unit and spread) with qualitative judgements about the information used and its scientific status (assessment and pedigree) (van der Sluijs et al. 2005). In this article, we will refer to this as unrepresentativeness.

NUSAP's pedigree approach was first introduced to the field of LCA by Weidema and Wesnaes (1996), the pedigree serving as a data quality indicator for LCIs. Later, it was also practically applied as a *quantitative* tool within the ecoinvent database, in order to produce estimates of uncertainty by attributing a set of uncertainty factors, based on expert judgement, to the pedigree *quality* indicators (Frischknecht et al. 2007). Uncertainty factors were first introduced by Huijbregts (1998b) as minimum and maximum estimates and later reinterpreted as geometric standard deviations, as almost all data were assumed to be log-normally distributed (Frischknecht et al. 2007). This quantitative use of the pedigree part of the NUSAP scheme, however, may be questioned with regard to its original intent and appropriateness, and it only ever estimates the unrepresentativeness of a dataset to its proposed use, thus excluding any inherent uncertainty or spread.

The work presented here is conducted as part of the ongoing Sustaining Ethical Aquaculture Trade project (SEAT;

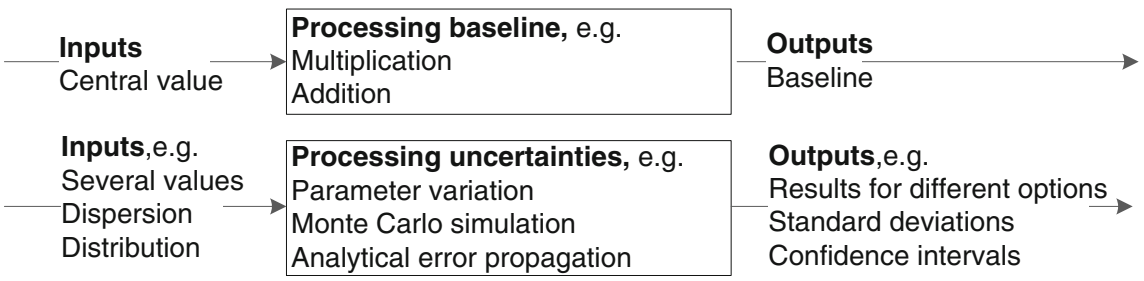

Fig. 1 Types of input parameters required to process point values or range outputs

Table 1 Definitions and examples of uncertainties originating from normal and post-normal science (Funtowicz and Ravetz 1990; Weidema and Wesnaes 1996; Huijbregts 1998a, b; Ravetz 1999; van der Sluijs et al. 2005)

Normal science (NUS)	Post-normal science (AP)
Inherent deviations and spread of data	Unrepresentativeness of data
Source: uncertainty and variability	Source: systems uncertainty and decision stakes
Including: parameter uncertainty, model uncertainty, spatial variability, temporal variability, variability between objects/sources	Including: Qualitative judgements, reliability, completeness, temporal correlation, geographical correlation and further technological correlation

www.seatglobal.eu), an EU FP7-funded collaboration project that aims to evaluate European imports of aquatic products from Asia. As an initial step of the project, an integrated survey was conducted to collect an extensive sample (n = 1,600 farms) of *primary data* (as defined in Table 2) for aquaculture farms in Bangladesh, China, Thailand and Vietnam. Additional primary data have also been collected for related processes, including feed mills, hatcheries, nurseries, processing plants, fishmeal factories and reduction fisheries (n = 10–40). With limited representation of Asian processes in available LCI databases, most supporting processes need to be modelled using *secondary data* (e.g. electricity production in Vietnam). Many secondary data sources, however, report inconsistent values and often lack information on inherent uncertainty ranges. In response to this—and in order to support SEAT's extensive primary dataset—we here propose a new, more consistent method for approaching and averaging data horizontally.

Table 2 Glossary of terms used throughout this study

Primary data	Data collected specifically for the intended study and representing relevant suppliers (UNEP 2011)
Secondary data	Previously published data describing processes for the intended study at different levels of aggregation and representativeness (UNEP 2011)
Unit process	Smallest element considered in the life cycle inventory analysis for which input and output data are quantified (ISO 2006)
Dispersion	Any form of range around a variable, resulting from inherent uncertainty, spread or unrepresentativeness
Inherent uncertainty	Uncertainties related to the inaccuracies of measurements or model at no level of horizontal averaging
Spread	Variability around an average resulting from horizontal averaging
Unrepresentativeness	Uncertainty resulting from the level of representativeness

The purpose of this manuscript is to propose a methodology for horizontal averaging of data where dispersion from inherent uncertainty, spread and unrepresentativeness is incorporated in the input parameters. The methodology was developed to allow for subjective unit processes to be produced, which can support the LCIs produced within the SEAT project.

2 Methods

Horizontal averaging of data is driven by many motives and goals, e.g. to comply with the goal of a study, ensure confidentiality, increase ease of use or provide computation efficiency (UNEP 2011). Given that each sample ideally should be handled as a unique unit process, the level of averaging should be kept to a minimum (UNEP 2011). However, out of practical reasons, both primary and secondary data almost always need to be averaged to some extent to make them manageable in the inventory phase. While averaging most often is discussed on a geographical level, as in Fig. 2, it also applies to technologies, seasons, scales of production, products (e.g. different varieties of crops), etc. As a direct result of averaging, the level of overall dispersion will generally increase, partially by spread and partially from unrepresentativeness. As processes often are presented on a global level (734 processes in ecoinvent v2.2), using average technology, or from different time periods, the importance of including dispersion is again highlighted.

Every sample of values can be described by a large number of moments, of which the first four (a central value, a variance, a coefficient of skewness and a coefficient of kurtosis) typically suffice to capture the main characteristics of the distribution. The estimates of these moments should be consistent, unbiased, efficient, sufficient, robust and practical (Morgan and Henrion

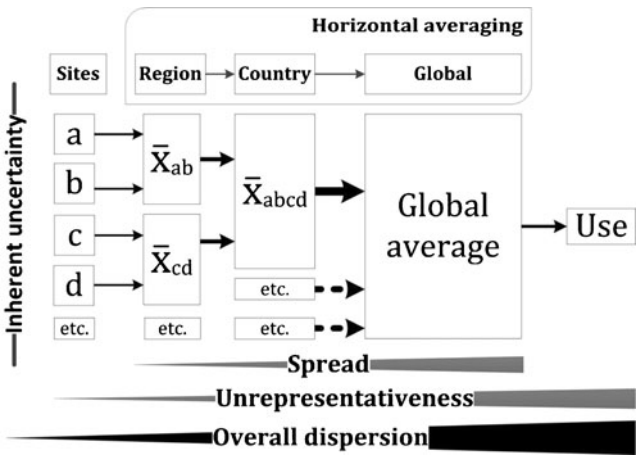

Fig. 2 The process of horizontal averaging displaying the cumulative effect on dispersion, originating from inherent uncertainty, spread and unrepresentativeness, using spatial averaging as a reference

1990). With focus on the practical, unit process data are often described by the two first moments fit to one of a limited number of distributions (e.g. normal, uniform, triangular and log-normal). While the central limit theorem states that the mean values of independent random variables are approximately normally distributed, multiplicative independent random variables tend to be log-normally distributed (Limpert et al. 2001). This, in addition to the desire to avoid negative numbers and to better represent large variances, explains the preference for log-normal distributions in LCI datasets. However, where sufficient data are available, the best fit distribution should be determined using a goodness-of-fit test for each dataset, as distributions based upon value choices may increase the data uncertainty it aims to describe. The choice of central value is, in the meantime, dependent upon the choice of software. The methodology described below will adopt the arithmetic mean as the central value, given that it is the input value in CMLCA. Correlating equations for geometric means are available as electronic supplementary material to this article. Dispersion measures should also correlate with the type of distribution (e.g. a geometric standard deviation to describe log-normally distributed data) and software used.

In order to apply the most appropriate moments to different sets of primary and secondary data, a decision tree was initially developed (Fig. 3). In the decision tree, priority is given to primary data (P1–3), assuming that they are more up to date and relevant, and provide a better level of understanding than secondary data. Where only one primary dataset is relevant (P3) to the scope of the study, spread can be neglected. However, if only one primary dataset is available (P3), the option of resolving to, or supplementing with, secondary data should be considered. For secondary data (S1–4), a weighting procedure amongst values is proposed, in order to acknowledge varying degrees of representativeness amongst secondary data sources. Where processes are unrepresented in literature (S4), four alternative options are suggested of which the one deemed to provide the most accurate estimate should be selected. The decision tree allows for more consistent data handling, while still partially relying upon expert judgement (particularly for secondary data) in order to approach the wide array of possible situations.

In order to more accurately determine the central value, we introduce a weighting procedure amongst secondary data points. The weighting procedure assumes that several reported values are available candidates for an inventory flow at the unit process level. The selection criteria for choosing values should be stated in the scope of the study, and the sample should preferably be well balanced (e.g. not all values from the same region). As each of the values will represent samples

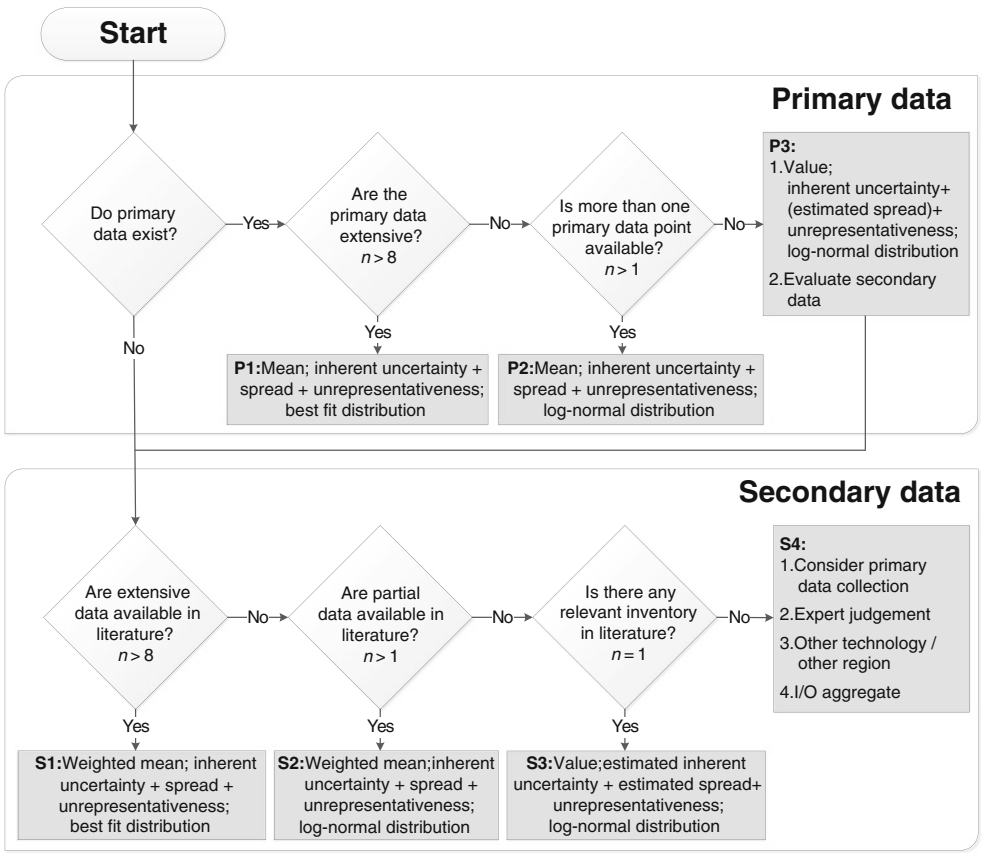

Fig. 3 Decision tree for sourcing unit process data, with regard to mean, inherent uncertainty, spread, unrepresentativeness and distribution

of different accuracy, we here encourage weighting based upon representativeness (σ^r), defined by the overall uncertainty factor, and inherent uncertainty (σ^u) where available for all values. This assures that more recent and extensive studies are given more emphasis, while also allowing for overlapping of inventories. Compiling and comparing data may also indicate if any cross-referencing exists amongst the secondary data sources, all of which should be removed from further analysis. Weighted means can be calculated using Eq. (1), where x represents the vector of n values indexed by i, w the weighting factors (Eq. 2) and $\overline{x}_{(wt)}$ the weighted arithmetic mean. For the input parameter (σ^{u+r}) in the weighting factor, we recommend the square of the arithmetic standard deviation. However, in order to avoid bias from the scale of means where relative uncertainty factors are adopted, and to allow for weighting of true zero values (e.g. no fish in pond x when the question is "how many fish are there in the pond?"), $1/\ln({\sigma_g}^{u+r})^2$ could be considered if relative geometric standard deviations are given or the square of the coefficient of variation $1/(\mathrm{CV}^{u+r})^2$ for relative arithmetic standard deviations.

$$\overline{x}_{(wt)} = \frac{1}{\sum w_i} \sum w_i x_i \tag{1}$$

$$w = \frac{1}{\left(\sigma^{u+r}\right)^2} \tag{2}$$

The estimate for representativeness can be derived from a NUSAP pedigree with accompanying uncertainty factors. The pedigree matrix should evaluate all of the most relevant variables, and its complexity may differ depending upon the ambition and complexity of the parameter/model assessed (van der Sluijs et al. 2005). Pedigree criteria should, moreover, be explicitly defined, to avoid interpretation bias and acknowledge that information on data sometimes is lacking for certain pedigree criteria. Uncertainty factors should meanwhile preferably be verified by real data. As an indicator for unrepresentativeness of weighted means, we recommend the use of the lowest uncertainty factor within a sample to characterise the unrepresentativeness of the weighted mean, given that this already has been accounted for in the weighting process.

As for inherent uncertainty, we naturally encourage the adoption of calculated arithmetic, or geometric (Eq. 3), standard deviations for primary site samples. Where standard deviations are reported around secondary data points, we recommend the adoption of the lowest reported inherent uncertainty, given the assumption that the increased sample results in more accurate values. Where inherent standard deviations remain unreported, estimates from related processes or basic uncertainties should be adopted. As for spread, the standard deviation amongst primary data values, or the values supporting each weighted mean, should be used.

$$\sigma_g = \exp\left(\sqrt{\frac{\sum_{i-1}^{n-1}\left(\ln\frac{x_i}{x_g}\right)^2}{n-1}}\right) \tag{3}$$

In order to aggregate the uncertainty factors, the standard deviations all need to be on the same scale. The translation of standard deviations between the normal (σ_a) and the log-normal scale is therefore presented by Eqs. (4) and (5). Both of these equations, however, only provide approximate parameters.

$$\sigma_a \approx \frac{\overline{x}}{2}\left(\sigma_g - \frac{1}{\sigma_g}\right) \tag{4}$$

$$\sigma_g \approx \sqrt{\frac{\overline{x}+\sigma_a}{\overline{x}-\sigma_a}} \tag{5}$$

Assuming that inherent uncertainty (σ^u), spread (σ^s) and unrepresentativeness (σ^r) are independent and moreover described on the same scale, the overall dispersion (σ^o) can be calculated using either Eq. (6) for arithmetic standard deviations or Eq. (7) for geometric standard deviations in accordance with the combination rules by Frischknecht et al. (2007). While Eq. (7) fulfils all the desired functions of combining geometric standard deviations, it is not universally recognised.

$$\sigma_a^{o^2} = \sigma_a^{u^2} + \sigma_a^{s^2} + \sigma_a^{r^2} \tag{6}$$

$$\sigma_g^{o^2} = \exp\left(\sqrt{\left[\ln\left(\sigma_g^{u^2}\right)\right]^2 + \left[\ln\left(\sigma_g^{s^2}\right)\right]^2 + \left[\ln\left(\sigma_g^{r^2}\right)\right]^2}\right) \tag{7}$$

Caution is needed with regard to zeroes on the log-normal scale, as negative or zero values for x are not accommodated. While missing values can be excluded from the equations, for true zero values, we recommend that they be substituted by a value of 10 % of the lowest non-zero value reported elsewhere for the variable. This ensures that the true zeroes remain the lowest value without introducing the complexity of, e.g. Box–Cox transformations (Ortiz and Arocha 2004). In cases where two alternative flows fill an identical function (e.g. generators and grid electricity), these may have to be treated individually with regard to their contribution. Templates for the recommended equations and unit process collection sheets are available as electronic supplementary material to this article.

3 A simple hypothetical example

In order to exemplify the proposed methodology, a hypothetical case will be used. Four values from secondary data sources (a–d) were assumed to represent a common unit process flow, each scaled towards a common reference flow, as is crucial before merging unit process data (Table 3). The pedigree and uncertainty factors proposed by Frischknecht et al. (2007) and Weidema et al. (2012) were adopted in order to evaluate unrepresentativeness. Both of these documents evaluate the categories of *reliability*, *completeness*, *temporal correlation*, *geographical correlation*, and *further technical correlation*, as originally proposed by Weidema and Wesnaes (1996), with the addition of sample size in Frischknecht et al. (2007). Sample size was again removed in Weidema et al. (2012), as default basic uncertainty factors were introduced. While the characteristics of the uncertainty factors in Frischknecht et al. (2007) are not always clear, we here assume these uncertainty factors to be equivalent with geometric standard deviations (σ_g). The representativeness of each value is reported within brackets as pedigree scores together with the corresponding summed relative uncertainty factors.

In accordance to Fig. 3, the decision tree, a log-normal distribution was assumed. Using the method described above (Eqs. 1, 2 and 4), the weighted arithmetic mean was derived at 1.479, adopting the uncertainty factors of Frischknecht et al (2007), and 1.654 when consulting Weidema et al. (2012) (excluding inherent uncertainties due to incomplete reporting). Alternative weighting factors resulted in weighted means of 1.585 according to Frischknecht et al. (2007) ($w_i=1/\ln({\sigma_g}^{u+r})^2$), and 1.671 according to Weidema et al. (2012) ($w_i=1/\mathrm{CV}^2$). All of these are higher than the basic arithmetic mean of 1.30, as a result of the two larger values (*A* and *B*) being more representative. To calculate the overall deviation, we adopt the proportionally lowest reported inherent uncertainty (${\sigma_a}^u=0.16$ or ${\sigma_g}^u\approx1.106$ using Eq. 5) and dimensioned pedigree estimate (${\sigma_a}^r=0.068$ (from ${\sigma_g}^r=1.041$) or 0.0017 (1.7×0.001)) amongst the values, depending upon the methodology used. The spread can be derived amongst the values to ${\sigma_a}^s=0.408$ or, alternatively, ${\sigma_g}^s=1.381$ (using Eq. 3). Finally, the overall dispersion can be estimated at ${\sigma_a}^o=0.443$ using Eq. (6) (assuming ${\sigma_a}^u=0.16$, ${\sigma_a}^s=0.408$ and ${\sigma_a}^r=0.068$) or ${\sigma_g}^o=1.406$ using Eq. (7) (and 5) (assuming ${\sigma_g}^i=1.106$, ${\sigma_g}^s=1.381$ and ${\sigma_g}^r=1.041$).

4 Discussion

Our proposed protocol presents a practical way to approach and organise primary and secondary data. While the procedure of critically evaluating data sources is time consuming, and resources often are limited, efforts can be restricted to the most influential parameters by initial scoping efforts and sensitivity analyses. By critically analysing the secondary inventory sources and weighting them towards a common mean, cross-referencing of outdated or estimated inventory flows is avoided. Horizontal averaging of data sources also allows for merging of inventories, thereby generating more complete unit process datasets. The proposed approach is especially useful for building more general processes, as primary data sources rarely represent national-level surveys, and production methods often differentiate geographically.

Defining and enclosing dispersion originating from inherent uncertainty, spread and unrepresentativeness is more fundamental than the choice of analytical method for propagating uncertainties (e.g. Monte Carlo analysis or Latin hypercube). To date, inherent uncertainties and spread have often been neglected or replaced by pedigree-generated uncertainty factors or default uncertainties. Even with the extension by Frischknecht et al. (2007), NUSAP's pedigree approach, however, only estimates unrepresentativeness of data and complements, rather than replaces, inherent uncertainty or spread. The above proposed methodology enables for dispersions to be estimated for both primary and secondary data. This provides one step towards producing more accurate ranges in LCI results, while clearer definitions of which uncertainty parameters should be embedded at the unit process level are encouraged.

While we here assume the arithmetic mean for the central value, this choice needs to be made in accordance with the specified data manager. In the meantime, the produced LCI outputs may better be represented by the geometric mean. More extensive statistical testing of LCI conclusions is also recommended, using, e.g. analysis of variance. To improve the level of detail of dispersions and results, we encourage

Table 3 A hypothetical list of values identified to represent a unit process flow

Source	a	b	c	d
Value	1.6	1.7	1.0	0.9
Reported inherent standard deviation	0.16	n.a.	0.12	n.a.
NUSAP score	(3, 2, 1, 2, 1; 2)	(2, 2, 2, 3, 1; 3)	(1, 3, 1, 3, 3; 2)	(2, 2, 4, 2, 4; 1)
Sum of squared uncertainty factors, σ_g (Frischknecht et al. 2007)	1.051	1.041	1.100	1.251
Sum of variances, σ_{CV} (Weidema et al. 2012)	0.002	0.001	0.008	0.041

underlying datasets of primary data to be made available, or at least to include sample size, standard deviations, and a distribution around presented means or other central values. Actual inherent uncertainties could then be calculated. Moreover, the application of NUSAP's pedigree should also be extended beyond the averaging of data and also apply to the point of use of that data. This becomes relevant (see Fig. 2) when using ecoinvent processes for purposes they are not intended to represent (e.g. using the ecoinvent product "rice, at farm [US, 2001–2006]" instead of Chinese rice in 2013).

The quantitative adaptation of the pedigree goes beyond its original intent, but is also the only way to evaluate the quality of the often more than 4,000+ processes commonly used in LCAs. We, however, encourage further advancements of the NUSAP approach within the field of LCA, especially the development of statistically supported uncertainty factors for individual sectors and/or regions, as categories of processes often experience inconsistent sensitivity towards the different types of correlation. For example, the rate of technological advancements in rapidly developing countries like China, or in high-tech industries (e.g. computer components), is often faster than in baseline cases (Williams et al. 2009). Its original function to evaluate uncertainties related to post-normal science should, however, not be forgotten. Moreover, the removal of sample size as an indicator based upon the introduction of default uncertainties may downplay its importance, especially for small samples. Sample size is a pivotal factor for any statistical model, but has so far played a relatively limited role in supporting LCA conclusions.

An expected advancement of ecoinvent v3 is parameterisation (Weidema et al. 2012), where raw data are made available for manipulation at the unit process level. The methodological advancements proposed here could be integrated in such parameterised LCI datasets to increase flexibility and transparency of data. Likewise, this protocol is useful when producing or adopting the surrogate global processes required in ecoinvent v.3. However, more support behind the background and characteristics of the scale independent normal distributions, adopted in the data quality guideline, is encouraged.

The current simplified approach for selecting inherent uncertainties and unrepresentativeness around weighted means was the result of limitations in reporting on data in literature, where advancements are welcomed. Moreover, the weighting factor proposed for arithmetic means (standard deviations) become biased (favouring smaller values) by the relative uncertainties often proposed in available quantitative adoptions of NUSAP's pedigree. Better justified mathematical approaches in the field of LCA as a whole are therefore recommended. Future efforts are also encouraged towards more frequent application of goodness-of-fit tests to extensive datasets, in order to identify which of the available distributions best characterise data categories. Moreover, the understanding and handling of covariance, where variables are correlated with each other, also remain limited. To date, as in this manuscript, covariance is often neglected which easily results in incorrect estimates of uncertainties when random sampling methods such as Monte Carlo are applied. Additional inaccuracy relates to the current benchmarking of temporal correlation to the time of data evaluation, where assessments of unrepresentativeness, in, e.g. databases, easily become outdated over time. Additional advances include the implementation of the Bayesian theorem where data are imputed (Björklund 2002) and meta-analysis of input data, rather than results (for more, please see the special issue on meta-analysis in J Ind Ecol (2012) 16:S1). Also, the advancement of statistical models, and introducing concepts such as statistical power, will allow for even stronger conclusions to be made and reintroduce the importance of sample size.

5 Conclusions

Increased objectivity and the inclusion of quantitative uncertainties are pressing issues in the field of LCA. If the community fails to address these issues, it may jeopardise its credibility and scientific integrity. While all the necessities today are available for the practical inclusion of uncertainties, greater efforts are needed to define the uncertainty parameters at the unit process level. For this, we have proposed a protocol for sourcing data, with the ambition of keeping the methodology amenable for the everyday LCA practitioner and limiting the resource investments needed. The protocol developed here is meant to help practitioners select the most representative and relevant data for their purposes and to quantify related uncertainties. To improve the quality of the data itself, improved reporting of primary data is necessary, as much of the underlying information on inherent uncertainties currently is lost somewhere in this reporting process. Hopefully, the next generation of parameterised inventories will encourage the reporting of raw data, instead of point values. In the meantime, better reporting on the underlying characteristics of data as online resource to articles is encouraged. The resulting unit process parameters from the methodology proposed herein, alongside other advancements in the field of LCA, will hopefully encourage more statistically rigid LCA conclusions.

Over the coming years, the here presented approach and the methodological considerations presented in Henriksson et al. (2011) will be implemented to evaluate a number of Asian aquaculture products exported to Europe, as part of the ongoing EU FP7-funded SEAT project. Additional advancements of the present methodology will also be made available in updated versions of the online resource of the present article (available at www.cml.leiden.edu/software/).

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